Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 109 (2022) 449–453

www.elsevier.com/locate/procedia

32nd CIRP Design 2022 (CIRP Design 2022)

Implementation of Artificial intelligence for maintenance operation in the rail industry

Ilesanmi Daniyan[a], Khumbulani Mpofu[a], Rumbidzai Muvunzi[a], Ikenna Damian Uchegbu[b]

[a]Department of Industrial Engineering, Tshwane University of Technology, Pretoria 0001, South Africa.
[b]Department of Mechanical & Mechatronic Engineering, Afe Babalola University, Ado Ekiti, Nigeria.

* Corresponding author. Tel.: +27727021931; Email: afolabiilesanmi@yahoo.com

Abstract

The quest to enhance maintenance operation in the rail industry has continued to occupy the front burner in recent time in a bid to reduce machine's downtime and ensure smooth operations. In this study, Artificial Intelligence (AI) technique was proposed for maintenance operation of wheel-bearing component of a railcar. Data from a secondary source was pre-processed and iteratively trained using specialised training algorithm in a machine learning environment under a supervised training until it produces a model capable of making predictions. The result obtained indicates the feasibility of the developed AI model for prediction of the Remaining Useful Life of a wheel-bearing component. The result shows that the wheel-bearing will last for 500 hours over the next 40 days before it begins to fail in service. The wheel bearing starts showing sign of degradation on day 41 of usage. Upon the use of the predictive model, the predicted RUL, confidence bound and slope detection instant were obtained. Hence, the implementation of AI for predictive maintenance could promote maintenance operation in the rail industry.

Keywords: AI; Machine learning; Maintenance operation; RUL; Wheel-bearing

1. Introduction

The rail industry has always been a frontier in mobility and technological advances. With the rapid and emerging technological advances in the industrial sector, technologies such as Artificial Intelligence, smart sensors and predictive maintenance can be deployed for the maintenance operations in the railway sector. This work enumerates the potentials of some technologies such as AI, smart sensor and predictive maintenance for maintenance operations in the rail sector. The deployment of this technology may promote the availability of rail infrastructures and prevent catastrophic failure of components in service. The implementation of these technologies is made possible through access to information and data in real time. The need to deploy some of these technologies to the rail sector stems from the fact that the rail sector are presently faced with some challenges that relates to maintenance operations, availability of rail system, interruptions of the supply chain activities, the need to improve on the real time monitoring and control. If these challenges are effectively addressed, it could promote the availability and reliability of the rail infrastructures, minimise unreliable scheduling and unrealistic forecast, and enhance improvement in ride comfort, safety and overall performance of the system.

Artificial intelligence also referred to as machine intelligence relates to the learning and problem solving capabilities of machines. It can acts as a driver for many innovations and emerging technologies in the rail industry. For instance, Artificial Intelligence (AI) find applications in pattern recognition, image processing, diagnosis, remote sensing, process planning and optimization, decision making and

2212-8271 © 2022 The Authors. Published by Elsevier B.V.

10.1016/j.procir.2022.05.277

VISIT…

LANZAROTE Caliente.COM

system control [1-3]. The capability of AI in system monitoring, fault diagnosis, identification of acoustic emissions, and predictive maintenance have been demonstrated [4-6]. The availability of data and use of machine learning algorithms for maintenance can promote productivity and decrease maintenance cost [7-9]. The machine learning approach can provide a means to learn from historical or present data so as to acquire necessary information needed to make predictions and decisions [10-13]. Hence, the use of AI systems can help in diagnosing the technical conditions of the railcar and tracking using the online mode (in real time) to obtain the system performance. Also, Artificial intelligence can be explored in railcar manufacturing for nonlinear prediction relating to traffic, and the condition of rail infrastructure. Furthermore, Artificial Intelligence system can be used to detect malfunctioning railcar components through audio signals. The input data into the neural network can be iteratively trained under supervised or unsupervised learning environment. Under the supervised learning, historical or present data can be trained to make future predictions about the health status of the component. Conversely, under the unsupervised learning environment the data acquired is usually trained to recognize and identify important features or trends relating to components health and failure with high level of confidence. The railcar operators now focuses on the development of intelligence systems for the early detection of faults or mechanical malfunctions before catastrophic failure. This offer predictive maintenance, real-time detection and diagnosis of faults, and remote diagnosis of equipment. Artificial intelligence also act as the building block of robotic solutions which can assist in the assembly operations, maintenance and repair works on railways.

Furthermore, the AI technology can also be deployed for the development of fully autonomous railcar with smart infrastructure components, which will permit the interconnectivity, and communication of the railcars with other systems. The AI can be employed for predictive maintenance in the railcar industry [14]. The second technology considered is the smart sensor. Smart sensors are the basic building blocks of the Internet of Things. The smart sensor comprises of an integrated system consisting of a sensor, micro-processor and communication technology which enables it to take measurements as input data, process it and communicate in real time. For instance, smart sensors such as load sensors, brake sensors, temperature wheel sensors etc. can be integrated into the railcar system for measuring critical parameters or conditions of the railcar system to develop an effective monitoring system for robust communication and diagnostic functions. This will foster effective monitoring of the health of the railcar in real time [14]. This will also decrease the failure rate and enhance the reliability of the rail, tracks, and signals. The data collected through the smart sensors can be extracted and processed through the use of dedicated algorithms and relayed as signals via the monitoring systems for quick decision making. Another technology considered in this study is the predictive maintenance. This is a continuous inspection and diagnosis function, which involves the estimation of failure times of individual parts of a system. This could reduce wasteful planning and maintenance activities, while also reducing failure of parts. Hence, predictive maintenance, can enhance better inventory management, eliminate unplanned downtime, while maximizing equipment lifetime. It can also bring about the reduction in maintenance cost, increase railcar availability while minimizing costly delays or interruptions thereby improving ride comfort and safety [15-18]. This can also significantly improve the efficiency, safety, and quality of fleet management and services through wireless and condition monitoring. The data gathered in real-time through the smart sensors with other monitoring software or devices can be used to develop predictive algorithm or models, which will provide information relating to the technical conditions of some railcar components like the bearings, wheels, and bogies etc. The continuous inspection and diagnosis support systems will assist operators in the quick intervention as regards maintenance operations before a catastrophic failure. The link among these three technologies; AI, smart sensors and predictive maintenance is that the smart sensors can be incorporated into critical components of the rail system for measuring the values of a certain parameter of the component in real time. From the measurements, data can be acquired over time which can be trained using AI algorithms. From the historical data trained, predictive models can be developed to predict the future behaviour of the system.

The aim of this study is to demonstrate the exploration of the AI and predictive maintenance geared towards maintenance operations in the railway sector. There is a need to embrace digital technologies to improve the operations, service and maintenance activities in the railway sector. The digital technologies encompasses the acquisition and analysis of digital data for maintenance purpose, reliable forecast and good decision making to improve the nature of the services rendered with improved customers' satisfaction.

The deployment of these digital technologies in the railway sector can promote safety, significant reduction in catastrophic failure of system and energy losses through real time monitoring. It can also enhance the operation, maintenance, and performance of the railcar with significant reduction in the maintenance related cost through predictive maintenance. Furthermore, it can give room for proper scheduling and realistic forecast leading to increased availability and reliability of the system. The use of these technologies can also provide information to enhance train performance optimisation and safety.

Hence, these benefits will promote the overall efficiency and performance of the rail sector. Kalathas and Papoutsidakis [19] reported on the application of predictive maintenance using machine learning and data mining. The outcome of the study indicates the suitability of achieving preventive maintenance through the machine learning approach.

Daniyan *et al.* [20] have reported on the suitability of the Artificial Intelligence system for enhancing product's performance during its life cycle in a railcar industry. Famurewa *et al.* [21] also stated that maintenance analytic can enhance e-maintenance and decision making in the rail industry. Not many works have been reported on the development of predictive maintenance based on AI. Hence, this is the major focus of this study with the aim to promote maintenance operations in the rail sector.

Figure 1 presents the integration of smart sensor, AI and predictive maintenance technologies. The figure illustrates how the three technologies can be incorporated for predictive maintenance. Smart sensors can be used for data acquisition while AI algorithm can be used for training before a predictive model can be obtained for future predictions.

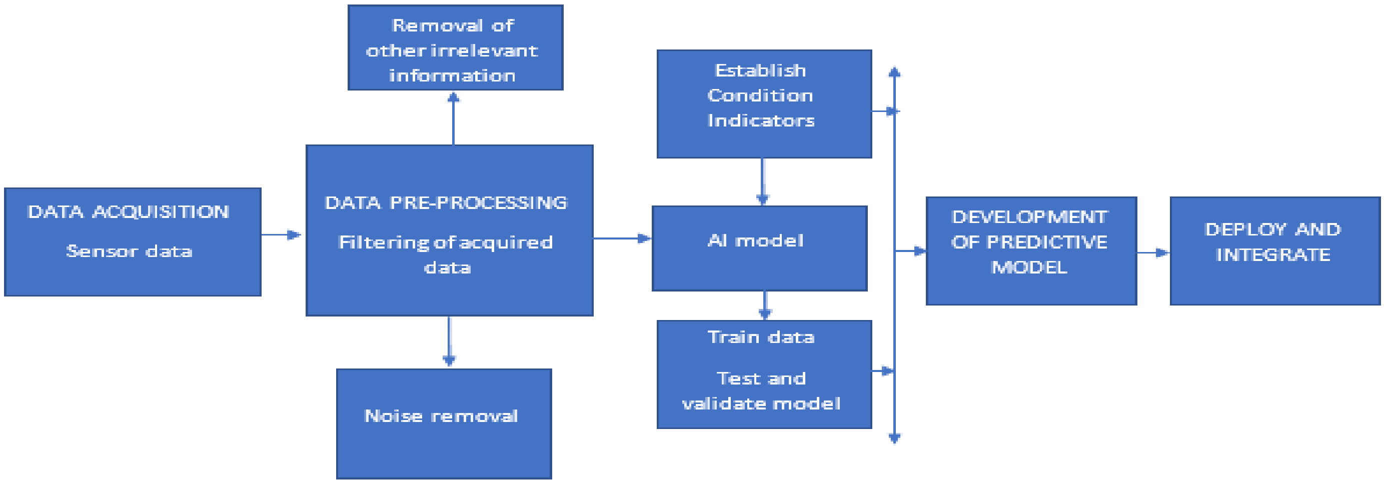

Figure 1. Integration of smart sensor, AI and predictive maintenance technologies

2. Methodology

The phases for the implementation of Figure 1 include the data acquisition, pre-processing, training and features extraction as well as the predictive model modules. The next module addresses data pre-processing to remove noise and bring it to a state where condition indicators can be extracted. The extraction of these features will enable participants to distinguish between the healthy and the faulty components. The next module explains the iterative training of the extracted feature in a machine learning environment to bring about a model which can detect anomalies, classify faults and estimate the remaining useful life of the component. The last module addresses the deployment of the developed algorithm and its integration into the system for component's monitoring and maintenance.

2.1 Data acquisition module

This deals with the acquisition of the relevant data which relates to the component to be maintained. Historical data about the health status specifically the wheel-bearing temperature data was acquired from secondary sources [14].
To obtain this data primarily, the incorporation of the smart sensor into the rail system can permit the acquisition of the important data that describes the health of the component. The effective deployment of the IoT, big data and cloud computing can also permit the acquisition, processing, storage and sharing of the acquired data.

2.2 Data processing module

Next, the acquired data are pre-processed and screened to ensure that only relevant data which describes the health status of the component are captured for further processing. The pre-processing involves filtering to remove noise and removal of other information that are not relevant to the health status of the component. At this stage, important features are extracted from the data which are necessary to describe the trend of the health status of the component over some period of time. The indicators of the health status of the components are also identified at this stage. This is necessary to detect components in the healthy, degradation and failure states.

2.3 Data training module

Under this module, the pre-processed data and the features extracted are iteratively trained using specialised training algorithm in a machine learning environment under a supervised or unsupervised training environment until it produces a model capable of making predictions or detecting anomalies. Following the pre-processing phase, the data was iteratively trained under a supervised learning environment in a MATLAB R2020b environment to predict the remaining useful life of the railcar wheel-bearing.

2.4 Model evaluation

Next is the performance evaluation of the model developed to determine its efficiency in making predictions and identifying anomalies. Statistical analysis involving Analysis of Variance (ANOVA), regression analysis and Mean Square Error check model can be performed on the developed model to determine its capability for predictive purpose. Random input variables which relates to the input data with which the model is trained can also be fed into the model to investigate the difference between the actual and predicted values by interpolation. A good model with predictive capabilities is usually identified with the closeness of the correlation coefficients R to 1, as well as the degree of agreement between the actual and predicted values [22].

2.5 Fault detection and prediction module

This module captures the training of decision models for condition based monitoring as well as fault detection. The model are trained to acquire the capability for fault detection and the prediction of the remaining useful life (RUL) of a component. Next to this is the implementation of the condition-based monitoring and predictive maintenance algorithms for maintenance purpose. The framework of the AI for predictive capabilities, which integrates the AI and other enabling technologies for predictive or condition based maintenance is presented in Fig. 2. Primarily, the smart sensor acts as the building block because, it is usually employed for capturing important measurement and information that relates to the health status of the component or system.

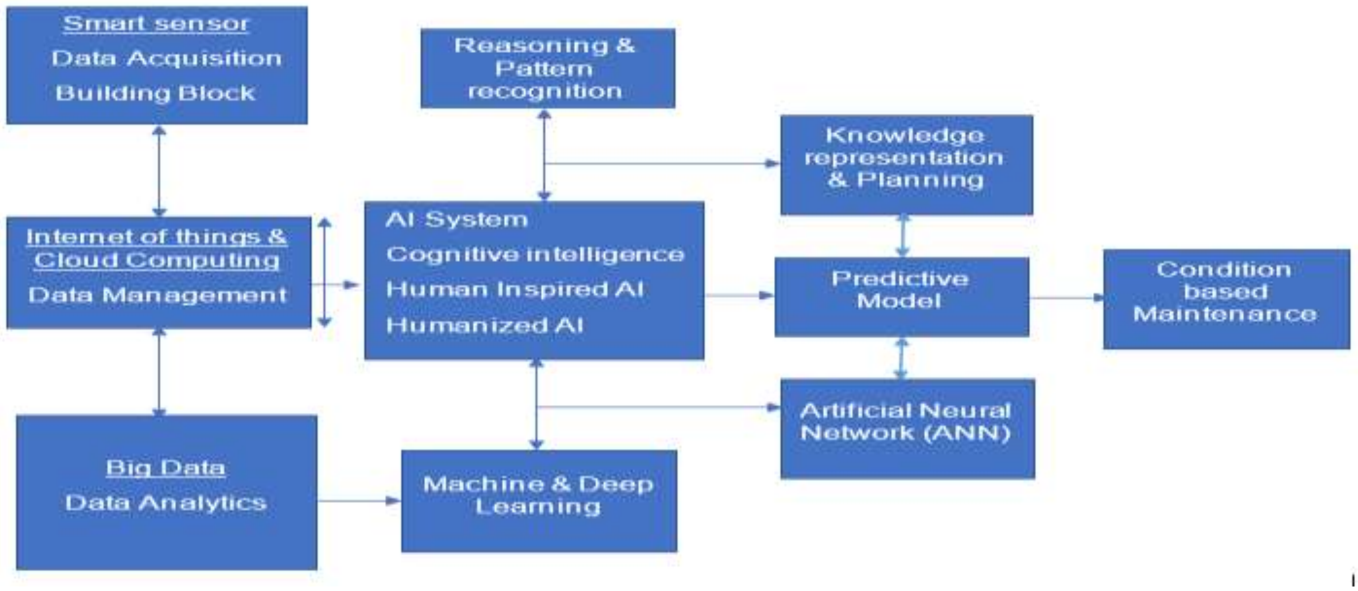

Fig. 2. AI with Predictive capabilities.

2.5. Performance evaluation of the predictive model

In this study, the performance evaluation of the predictive model developed was carried out. The details of the data acquisition, preprocessing and training have been reported in Daniyan *et al.* [14]. The performance evaluation reported in Daniyan *et al.* [14] was limited to the predicted temperature-time plots. Hence, this study reports the RUL of the wheel-bearing component. The indicator for the predictive model in this study is the Remaining Useful Life (RUL) of the wheel-bearing component. The RUL of a component is the remaining useful time or the expected life before maintenance operation (repair or replacement) is carried out. The development of a predictive model is a central objective of predictive-maintenance algorithms. The useful time is the life expectancy of the component as a function of time (measured in hours or day) since the start of operation. The estimation of the RUL of the component was done based on the development of a predictive model, and time estimates.

The predictive model fits the time evolution of a health indicator (degradation) and predicts the time taken for the health indicator to exceed the pre-set threshold value. This is indicative of a faulty condition which over time can lead to a catastrophic failure. Thereafter, the model predicts the RUL which is the most likely time-to-failure of the component. The predictions from this model are estimates with associated uncertainties. Although it provides a probability distribution of the RUL of the component but assumes that the component is used under the same condition throughout its useful life.

3. Results and Discussion

Fig. 3 and 4 present the degradation model RUL of a wheel bearing. The estimated RUL value is computed once a slope is detected in the plot. As the slope appears, the RUL decreases over time and the confidence bounds on the predicted RUL become narrower over time.

The result show that the wheel bearing will last for 500 hours over the next 40 days before it begins to fail in service. The results agree significantly with the the predicted temperature-time plots of the fourth bearing reported by Daniyan *et al.* [14]. According to results of the temperature-time plots presented by Daniyan *et al.* [14], the first three bearings show signs of failure but the fourth bearing did not show any sign of failure and this prompted the need for the determination of the RUL sudden failure in service. The results show that the wheel bearing starts showing sign of degradation on day 41 of usage (Figure 3). Upon the use of the predictive model, the predicted RUL, confidence bound and slope detection instant were obtained as shown in Figure 4.

Figure 4 shows that the maximum estimated RUL of the wheel-bearing is 505 hours. This implies that the maximum expected life or RUL of the bearing is 21 days before repair or replacement for a continuous operation of 24 hours. Since the expected period of operation of the wheel-bearing is assumed to be limited to 12 hours per day, then, it can be concluded the RUL of the wheel bearing is 42 days as indicated in Figure 4.

Figure 5 shows the probability density function of the RUL of the wheel-bearing. It is used to indicate the probability that the value of the RUL will fall within a particular range of values. From Figure 5, it is evident that there is a probability that the RUL value falls within the range of 25-95 days by approximation.

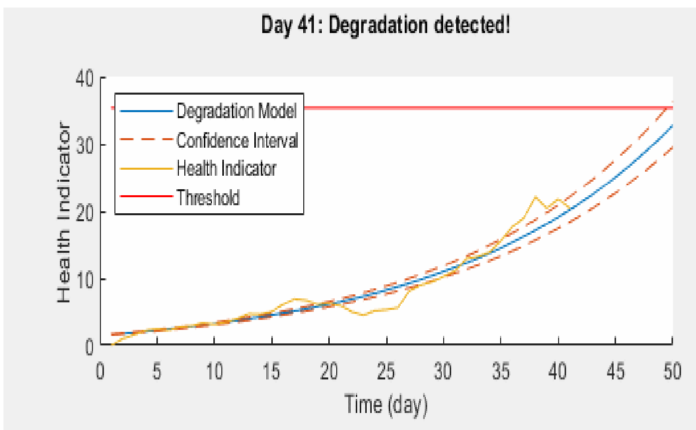

Fig. 3. Degradation model of the wheel bearing.

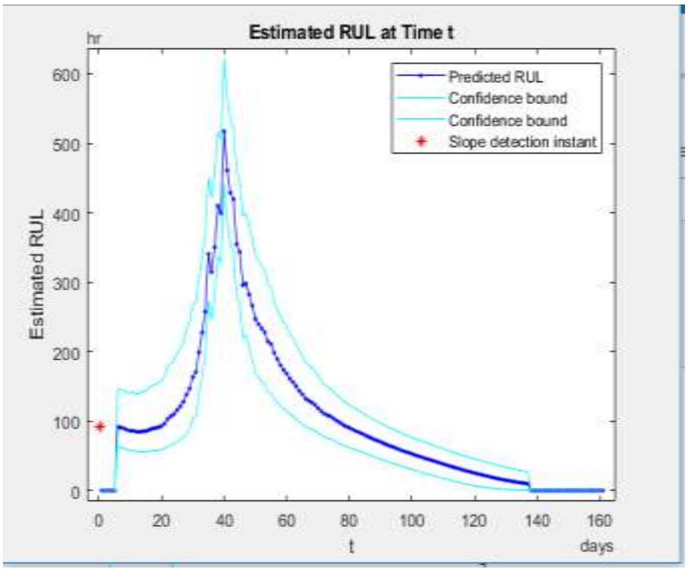

Fig. 4. The RUL of the wheel bearing.

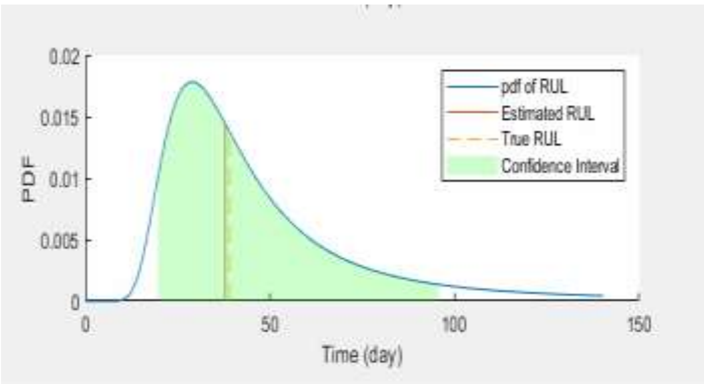

Fig. 5. The probability density function of the RUL of the wheel bearing.

4. Conclusion

This study has proposed the integration of smart sensor and AI technology for predictive maintenance in the rail sector. The identified technologies can provide satisfactory digital solutions to maintenance issues in the rail industry. If adequately deployed, it has the potential to revolutionize the maintenance operation of railcar systems, leading to rapid transformation of the sector. The performance evaluation of the AI technology for predictive maintenance was also in the study. The result obtained indicates the feasibility of the developed AI model for prediction of the Remaining Useful Life of a wheel-bearing component of a railcar. The result show that the wheel bearing will last for 500 hours over the next 40 days before it begins to fail in service. It is recommended that the rail industry and the regulatory agencies act now by embracing these innovations and adjusting their business model to accommodate these disruptive technologies to gain a competitive advantage, and emerge as frontiers in line with the global best practices. Once a reliable estimates for the RUL of critical components are obtained, it can be integrated into the system's dashboards or incorporated into alarm systems for continuous monitoring by operating personnel or maintenance teams.

ACKNOWLEDGEMENTS

Funding: The authors disclosed receipt of the following financial support for the research: Technology Innovation Agency (TIA) South Africa, Gibela Rail Transport Consortium (GRTC), National Research Foundation (NRF grant 123575) and the Tshwane University of Technology (TUT)."

References

[1] Bostrom, N. 2014. Superintelligence—Paths, Dangers, Strategies; Oxford University Press: Oxford, UK, 2014.
[2] Klumpp, M. 2017b. Artificial Divide: The New Challenge of Human-Artificial Performance in Logistics. In Innovative Produkte und Dienstleistungen in der Mobilität; Proff, H., Fojcik, T.M., Eds.; Springer Gabler: Heidelberg/Berlin, Germany, pp. 583–593.
[3] Armstrong, S., Bostrom, N., Shulman, C. 2016. Racing to the precipice: A model of artificial intelligence development. *AI Soc.* 31, 201–206.
[4] Silver, D., Schrittwieser, J., Smionyan, K., Antonoglou, I., Huang, A., Guez, A., Hubert, T., Baker, L., Lai, M., Bolton, A. 2017. Mastering the game of Go without human knowledge. *Nature* 550, 354–359.
[5] Kosir, A. and Strle, G. 2017. Emotion Elicitation in a Socially Intelligent Service: The Typing Tutor. *Computers* 6(14).
[6] Klumpp, M. 2017b. Artificial Divide: The New Challenge of Human-Artificial Performance in Logistics. In Innovative Produkte und Dienstleistungen in der Mobilität; Proff, H., Fojcik, T.M., Eds.; Springer Gabler: Heidelberg/Berlin, Germany, pp. 583–593.
[7] Ran, Y., Zhou, X., Lin, P., Wen, Y., Deng, R. A 2019. Survey of Predictive Maintenance: Systems, Purposes and Approaches. arXiv 2019, arXiv:1912.07383.
[8] Michalski, R. S., Carbonell, J. G., Mitchell, T.M. 2013. Machine Learning: An Artificial Intelligence Approach; Springer: Berlin, Germany, 2013.
[9] Kyrkos, E. 2015. Business Intelligence and Data Mining; Hellenic Academic Libraries Link: Athens, Greece, 2015; Chapter 4.
[10] Rokach, L. and Maimon, O. 2013. Data Mining with Decision Trees; World Scientific Pub Co Pte Ltd.: Singapore, 2013.
[11] Shin, J.-H.; Jun, H.-B. 2015. On condition based maintenance policy. *J. Comput. Des. Eng.* 2, 119–127.
[12] Bousdekis, A., Apostolou, D. and Mentzas, G. Predictive Maintenance in the 4th Industrial Revolution: Benefits, Business Opportunities, and Managerial Implications. *IEEE Eng. Manag. Rev.* 2020, 48, 57–62.
[13] Sakib, N. and Wuest, T. 2018. Challenges and opportunities of condition-based predictive maintenance: A review. *Procedia CIRP*, 78, 267–272.
[14] Daniyan, I. A., Mpofu, K., Oyesola, M., Ramatsetse, B. I. and Adeodu, A. O. 2020. Artificial Intelligence for Predictive Maintenance in the Railcar Learning Factories. *Procedia Manufacturing,* 45:13-18.
[15] Gunsekaran, A. and Ngai, E. W. T. 2014. Expert systems and artificial intelligence in the 21st century logistics and supply chain management. *Expert Syst. Appl.* 41, 1–4.
[16] Alawad, H. and Kaewunruen, S. 2018. Wireless sensor networks: toward smarter railway stations, Infrastructures 3, 24:1-17.
[17] Rogers, P. 2018. Why cloud is key to unlocking rail industrial growth. Available at https://www.intelligentcio.com/africa/2018/08/07/why-cloud-is-key-to-unlocking-rail-industry-growth/. Retrieved on 26th August, 2020.
[18] Montreuil, B. 2011.Towards a Physical Internet: Meeting the global logistics sustainability Grand challenge. *Logist. Res.* 3, 71–87.
[19] Kalathas, I. and Papoutsidakis, M. 2021 Predictive maintenance using machine learning and data mining: a pioneer method implemented to Greek railways. Designs, 5(5):1-18.
[20] Daniyan, I. A., Muvunzi, R. and Mpofu, K. 2021. Artificial Intelligence System for enhancing product's performance during its life cycle in a railcar industry, *Procedia CIRP,* 98:482-487.
[21] Famurewa, S. M., Zhang, L., Asplund, M., Duffuaa, S. and Parida, A. 2017. Maintenance analytics for railway infrastructure decision support. *J. Qual. Maint. Eng.* 23, 310–325.
[22] Daniyan, I. A., Tlhabadira, I., Mpofu, K. and Adeodu, A. O. (2020). Development of numerical models for the prediction of temperature and surface roughness during the machining operation of titanium alloy (Ti6Al4V). *Acta Polytechnica Journal,* 60(5):369–390, 2020.